Correlation Controlled Bilateral Filtering of fMRI Data

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Introduction

In analysis of fMRI data, highly sensitive detection of activated voxels is needed. The high noise levels in typical fMRI data makes this impossible to achive without pooling data from several voxels before the signal detection. The most common approach, applied in for instance SPM [1], is to employ spatial lowpass filtering (using a fixed filter kernel) of the data prior to the detection of active voxels. This is done under the assumption that in most small neighborhoods, either almost all or almost no voxels are part of an activated region. Naturally, this causes blurring of the edges of activated areas, and depending on the chosen threshold either causes regions of detected activation to shrink or grow. Another method, proposed by Friman et al [2], uses canonical correlation analysis (CCA) to adaptively find a spatial lowpass filter that maximizes the similarity between the filtered data and the model of the blood oxygen level dependent (BOLD) signal. However, it is equally important to correctly classify inactive voxels, and maximizing the similarity in each neighborhood may cause voxels close to the boundary of an active region to be falsely declared as active.

To alleviate these problems, we propose an edge-preserving method for adaptive filtering of fMRI data. The proposed method is similar to bilateral filtering [3], but instead of image intensity, a correlation measure, related to mutual information, between individual time series and the BOLD model is used as distance measure for the range filters.

Theory and proposed method

In bilateral filtering, the filter kernel in each neighborhood can be expressed as a product of two filter kernels: the domain filter F_d and the range filter F_r. The domain filter is based on spatial distance while the range filter is based on the difference in image intensity. That is, given an image *I(x, y)*, the bilateral filter kernel *F(i, j)* at image coordinates *(x, y)* can be written

$F(i,j) = F_d(i,j) \cdot F_r(i,j)$, where $F_d(i,j)$ is an ordinary spatial filter kernel $g(i,j)$ and the range filter is defined as $F_r(i,j) = h(I(x+i, y+j) - I(x,y))$.

A common choice of the filter kernels *g* and *h* is Gaussian functions, and that is also what we propose here. Godtliebsen et al [4] have proposed using bilateral filtering of the raw fMRI data, with a time dimension in addition to the spatial and range dimensions described above. What we propose here is similar to bilateral filtering, but instead of creating the range filter from differences in image intensity, we use the difference in correlation between the individual voxel timeseries and the BOLD model. This means that voxels with similar correlations will be averaged together. Furthermore, instead of using the correlation coefficient directly, we use a mapping, known as Wilks' lambda, of the correlation. Under certain conditions this measure is equivalent to mutual information. Hence,

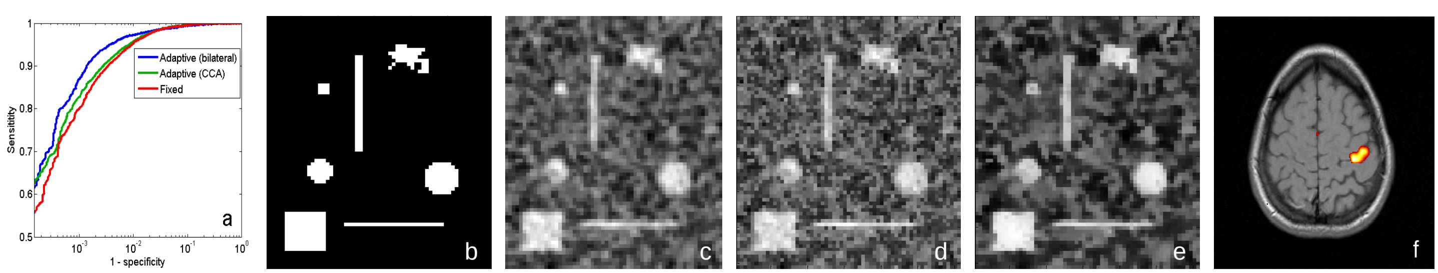
$F_r(i,j) = h(M(x+i, y+j) - M(x,y))$, where $M = \log(1/(1-\rho^2))$ and ρ is the correlation coefficient.

Assuming that the initial correlation estimate is good enough, in each neighborhood this yields a filter *F(i, j)* that averages over voxels with similar level of activation. These filters are then used to filter the raw data in each timepoint, after which each voxel in the resulting data is analyzed separately to detect activation. It is important to notice that this is different from calculating the correlation in each voxel and then performing bilateral filtering of the correlation map. The BOLD model used here is a linear subspace model, based on principal component analysis of several plausible BOLD responses generated using Buxton's balloon model [5].

Results and discussion

The proposed method has been evaluated on both real and synthetic data. Figures c-e show correlation maps generated from simulated data using fixed lowpass filtering, adaptive filtering using CCA and adaptive filtering using the proposed method, respectively. The areas where BOLD-like signals were embedded in the noise are shown in figure b. In figure a, receiver operating characteristic (ROC) curves, showing the sensitivity (ability to correctly classify active voxels) versus the specificity (ability to correctly classify inactive voxels) of the different methods, are shown. The signal to noise ratio of the simulated data is approximately 5 %. Figure f shows activation detected in real data from a finger tapping task, overlaid on an anatomical image of the brain. The activation in the motor area is consistent with the task, but since the ground truth is unknown, it is difficult to use real data to evaluate a detection method.

It is evident from the ROC curves that the presented method has superior ability to discriminate between active and inactive voxels in the simulated data. This is also supported by the correlation map in figure e, which shows sharper edges between active and inactive regions than the correlation maps generated by the CCA method and the method based on a fixed filter. This edge-preserving property is clearly an advantage of the proposed method. Although the method is here presented for two-dimensional filtering, a generalization to three dimensions is trivial and expected to further improve the results.



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